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ABSTRACT

This paper briefly explains the possible two-mode techniques of factor analysis, and discusses, in more detail, one two-mode technique--the Q-technique. The Q-technique may be useful when the researcher is interested in obtaining information about "types" of individuals with regard to certain variables. A concrete heuristic example is used to illustrate Q-technique factor analysis. In this example, a structured Q-sort was developed based on the student appraisal criteria used to classify students for special education services. Q-sort data consisted of the scores of eight students, classified as emotionally disturbed; the scores were received when the teacher rated the students on each of 18 variables. The data were then factor analyzed to determine the factors or clusters of the students across the variable replicants. Two factor extraction methods, principal components and principal factors, were used and the factors were rotated using the varimax procedure. The use of factor scores to facilitate interpretation of person factors is then illustrated. Eight data tables and five data plots are provided. The Q-technique data file and the command file used to analyze the Q-technique data are appended. (Author/TJH)

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The Use and Interpretation of Q-Technique Factor Analysis

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Abstract

This paper briefly explains the possible two-mode techniques of factor analysis and discusses in more detail one two-mode technique, Q-technique, which may be useful when the researcher is interested in obtaining information about "types" of individuals with regard to certain variables. A concrete heuristic example is used to illustrate Q-technique factor analysis. In this example, a structured Q-sort was developed based on the pupil appraisal criteria used to classify students for special education services. Q-sort data consisted of the scores eight students, classified as emotionally disturbed, received when the teacher rated them on each of 18 variables. The data were then factor analyzed to determine the factors or clusters of the students across the variable replicants. Two factor extraction methods, principal components and principal factors, were employed and the factors were rotated using the varimax procedure. The use of factor scores to facilitate interpretation of person factors is then illustrated.

The Use and Interpretation of Q-Technique Factor Analysis

Factor analysis is an analytic technique commonly used to examine the interrelationships among variables. Factor analysis may be used as an exploratory technique to identify underlying constructs or as a reductive technique to condense a large number of variables into a smaller number of "underlying" variables which retain most of the information in the larger, original variable set. Another important purpose of factor analysis is to test specific theory-based hypotheses about the relations among variables.

Before a specific application of factor analysis is explained and illustrated here, some issues more generally relevant to factor analytic design will be presented. Cattell (1966) discussed possible techniques of relational analysis in the behavioral sciences, and proposed a Basic Data Relation Matrix or "data box" to conceptualize the available techniques. Based on this notion of a "data box," three aspects, subjects, variables, and occasions or times of measurement, can be used to characterize the data in a study. While it is possible to design studies in which all three dimensions are investigated (e.g., Thompson & Miller, 1978), typically researchers investigate only two dimensions, while the third is held constant. Therefore, six possible two-mode techniques of factor analysis have been delineated from the combinations of data aspects.

Typically in factor analysis a two-dimensional data

matrix is analyzed with the columns of the matrix representing different variables and the rows incorporating the scores of individuals on those variables. Thus, the analysis is based on correlations among variables computed across individuals, and represents what Cattell (1966) labelled R-technique factor analysis. Factor analysis may also be used to examine correlations among people computed across variables, and this analysis is called Q-technique. When the two modes to be analyzed are variables and occasions of measurement, correlations can be computed among variables across occasions of measurement, with the subject of the study being a single person or data object, and this is termed P-technique factor analysis. Or correlations can be computed among occasions across a series of variable scores, and this is termed O-technique factor analysis. When the two modes to be analyzed are individual subjects and occasions of measurement, with the variable held constant, correlations can be computed between occasions across a sample of individuals, and this is called T-technique factor analysis. Or correlations can be computed between subjects across a series of occasions of measurement of a single variable, and this is called S-technique factor analysis.

The present paper focuses on an application of Q-technique factor analysis. Kerlinger (1973) described Q-technique as "a sophisticated way of rank-ordering objects (items, stimuli, etc.) and then assigning numerals to subsets of the objects for statistical purposes" (p. 582).

Q-technique has been referred to as "inverse" analysis (Comrey, 1973) and as "transposed" or "inverted" analysis (Nunnally, 1967).

Stephenson (1953) discussed applications of Q-technique in the study of personality, social psychology, and clinical psychology. He proposed that it may be more important to examine relationships among people rather than relationships among variables. Q-technique may be helpful, for example, in investigating clusterings of people based on variables such as attitudes, preferences, or thinking behavior. Kerlinger (1973) suggested that Q-technique could be used to open up new research areas, to explore hunches and to test preliminary theories. In Q "one tests theories on small sets of individuals carefully chosen for their 'known' or presumed possession of some significant characteristic or characteristics. One explores unknown and unfamiliar areas and variables for their identity, their interrelations, and their functioning" (p. 598).

More recently, Thompson (1980) used Q technique to investigate the validity of a fourfold typology of evaluators. Professional evaluators in a school district were categorized by their immediate superiors as one of four types of evaluators: Technicians, Politicians, Entrepreneurs, or Pretenders. Each evaluator then participated in a modified Q-sort task in which they rank ordered statements identified as characteristics of this theory's specifications of evaluator types. A Q-technique

factor analysis was employed to evaluate the theory.

Similarly, Townsend (1987) investigated the manner in which faculty, medical librarians, media producers, and instructional designers make decisions about the types of media to be used in medical education. He developed, validated and revised a Media Selection Inventory using R-technique factor analysis. Townsend then had various individuals representing these same functions in professional education respond to the revised Inventory and he analyzed their responses using Q-technique factor analysis. In summary, the use of Q-technique to study human behavior seems to have wide application.

Q-Technique Data Collection

Typically, Q-technique involves a sorting procedure, called a Q-sort, and the correlation of responses of individuals to the Q-sorts. A sample of stimuli from a specifible universe of content are given to a subject for sorting. The subject is directed to sort the set of objects (i.e., verbal statements, single words, phrases, pictures) by putting varying numbers of cards or stimuli into several piles between two extremes. The number of cards to be assigned to each pile is based on a predetermined symmetrical distribution. Thus, a rank-order continuum is developed with extremes labeled, for example, "Most Approve" to "Least Approve," "Most Like Me" to "Least Like Me," or "Prefer Most" to "Prefer Least." Because subjects are required to distribute their responses in terms of a fixed distribution,

usually an approximately normal distribution, all subjects will have exactly the same mean rating, the same standard deviation of ratings, and the same distribution of ratings.

Typically a Q-sort may contain 60-120 cards. Kerlinger (1973) recommends that at least 60 cards be used for statistical stability and reliability. Thompson (1981) has proposed that the number of items needed for a Q-sort is a function of the number of individuals to be studied. According to Thompson, the minimum number of items required in a Q-sort can be determined with the following formula:

(# of items)/2 - 1 >= # of participants.

When a Q-sort is used, it is important to consider how the stimuli to be sorted are selected. Instead of a sampling of people, the researcher is concerned with a sampling of stimuli. While it seems clear that all stimuli need to come from some common frame of reference, Nunnally (1967) asserts that there are problems in defining "populations" of stimuli.

One way in which the researcher can generate a structured sample of items is to use the variables of a "theory" or hypothesis in selecting the items to be included. In this approach the "theory" the researcher wishes to test is built into the Q-sort. The Thompson (1980) study provides an example of the way in which Q-technique can be used to test theory using a structured sample of sorted stimuli.

If it is difficult to generate a sensible structured sample, the researcher may "randomly sample" the desired number of things to be used in a Q-sort. When random samples

are used, this method is called an unstructured Q-sort. Kerlinger (1973) defined an unstructured Q-sort as "a set of items assembled without specific regard to the variables or factors underlying the items" (p. 587). In an unstructured Q-sort a large number of items are selected that are assumed to measure one broad variable, for example, attitudes toward the handicapped. Given a theoretically infinite population of items, the hope is that the researcher will select a set of items for the Q-sort that are a representative sample of the item population (Kerlinger, 1973, p. 587). Kerlinger reports that this approach has dominated Q studies.

The Q-technique may be useful when the researcher is interested in obtaining information about "types" of individuals with regard to certain variables. Factor analysis then allows the researcher to derive factors or clusters of people, as against the R-technique clustering of variables.

A Heuristic Example

A concrete heuristic example of a structured Q-technique factor analysis may be useful. Q-sort data for this example consisted of the scores eight students received when their teacher rated them on each of 18 variables. The data were factor analyzed to determine the factors or clusters of the eight students across replicants of the 18 variables.

The purpose of the study was to determine whether the use of certain criteria for classifying students into special education categories results in groupings of similar

students. Specifically, if the same definition of emotional disturbance is used by external authorities to classify students and to determine eligibility and placement for special education services, then it might be expected that the different students should cluster together according to these diagnostic criteria.

The instrument consisted of 18 statements which the teacher sorted according to how strongly she agreed the statements were descriptive of the students. An individual Q-sort was completed for each of the eight students in the class. The 18 statements were selected from the pupil appraisal criteria used in the state of Louisiana to classify students as "behavior disordered/emotionally disturbed," "learning disabled," "mild mentally retarded," and "slow learner." These categories constituted the structure underlying the Q-sort.

Results and Interpretation

Table 1 presents the correlation matrix among all eight subjects across the profile of variables. An examination of the correlation matrix shows that half of the coefficients are greater than 0.3 in absolute value. Therefore, it seems likely that some of the students can be clustered into subsets.

When different extraction procedures are used, and the same answers are obtained, results may be considered invariant, that is, replicable. Thus, in actual research researchers may employ several extraction methods and may

vary the number of factors extracted.

Initially, a principal components analysis was used to extract factors from the correlation matrix. In principal components analysis, an assumption is made that the reliability of each factored entity is one or close to one. Therefore, the principal components are extracted from a correlation matrix with ones on the diagonal, a reflection of the presumption of perfectly reliable measurement. In the present analysis all factors with eigenvalues greater than one were extracted. The three extracted factors explained 75.8% of the total variance among the eight students. Table 2 presents the unrotated factor matrix. The coefficients in this matrix are called pattern coefficients and indicate how much weight each person was assigned in relation to each factor. Because the estimated factors are uncorrelated ("orthogonal"), these pattern coefficients are also the correlations between the variables and each factor, and are also called structure coefficients. Table 3 presents what was left of the correlation matrix after factor extraction, and also the components of the correlation matrix that can be reproduced by the factors.

In order to improve the interpretability of the factors derived from the data, factors were rotated using the varimax procedure. Table 4 presents the factor matrix after varimax rotation. Interpretation of the rotated factor matrix suggests that only four of the subjects (S2, S3, S5, and S6) are close to being "pure" types as defined by the three

factors presented in Table 4. It is also possible to plot the persons using the factor structure coefficients as coordinates, to assist in interpretation. If simple structure is achieved, clusters of people should occur at the end of the axes of any pair of factors. An examination of Figures 1, 2, and 3 suggests that several of the subjects are associated with two or more types.

Given these results, a second extraction procedure was used to analyze the data. Principal factors analysis is similar to principal components analysis except that the diagonals of the correlation matrix are replaced by estimates of communalities, that is, lower bound estimates of reliability. Communalities continue to be reestimated as factors are extracted repeatedly until communality estimates stabilize or converge. However, when principal factors analysis was used in this study, communality estimation for three factors did not converge even after 25 iterations. The first two factors accounted for 53.7% of the total variance among people. The third factor had an eigenvalue of .78 and accounted for an additional 9.7% (.78/8) of the variance.

A new principal components analysis was then performed with only two factors being extracted, and the unrotated matrix for this solution is presented in Table 5. These two factors accounted for 62.5% of the variance among the eight subjects. With a two-factor solution, after varimax rotation, as reported in Table 6, four of the eight subjects

(S3, S4, S5, and S7) appeared highly related to Factor I, while two subjects (S2 and S6) appeared highly and "univocally" related to Factor II. The remaining two students (S1 and S8) appear to share characteristics of both person types. Interpretation can be facilitated by examining a plot of structure coefficients, and this plot is reported in Figure 4.

When two factors were extracted using principal factors analysis, 12 iterations were required for extraction to converge. These two factors accounted for 51.5% of the variance. A similar solution was obtained after varimax rotation, as suggested by Figure 5.

Further interpretation of Q-technique results is facilitated by obtaining factor scores. With principal components analysis, unlike principal factors analysis, mathematically exact factor scores can be obtained. Table 7 presents the factor scores obtained from the two-factor principal components analysis. The factor scores can be consulted to determine which of the 18 statements provide a basis for defining and differentiating the two clusters of students. Table 8 presents the most relevant statements and factor scores. Statements with high positive scores reflect strong agreement while statements with high negative scores indicate strong disagrement. Factor I scores suggest that this "pure" type of student can be characterized as a "streetwise" disadvantaged youth exhibiting uneven academic performance. Factor II scores suggest that this "pure" type

of student represents the classic definition of emotional disturbance reflected by inappropriate behavior or feelings displayed over an extended period of time and to a significant degree, and lower levels of adaptive behavior in comparison to age peers.

An examination of the third column of Table 8 indicates that the two groups of students differed most on whether the teacher believed their handicap to be primarily due to environmental, cultural, or economic disadvantage. The groups also differed on levels of academic performance (uneven performance vs. lower performance across all academic subjects), and apparent degree of age-appropriate adaptive behavior.

Summary

Q-technique factor analysis is used to examine correlations among people computed across variables. Q-technique has been used to investigate clusterings of people based on variables such as attitudes, preferences, and thinking behavior. With Q-technique factor analysis it is possible to obtain factors which can be thought of as idealized "types" of persons. Teachers of special education students would benefit from knowing which "types" of students, within a specific diagnostic category, are enrolled in their classes. In this example, results suggest that even though all eight students had been classified as emotionally disturbed by external authorities on the basis of pupil appraisal criteria, the teacher perceived two distinct

types of students. The "type" of students in a class will have implications for instructional planning and classroom management. Thus, there are times when it is more important to be concerned with clusters of people, rather than with clusters of varibles, and Q-technique factor analysis can be useful in these situations, as illustrated here.

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Table 1

Correlation Matrix

	S1	S2	S3	S4	S5	S6	S7	S8
S1	--							
S2	.58333	--						
S3	.16667	.29167	--					
S4	.33333	-.08333	.41667	--				
S5	.33333	.04167	.08333	.20833	--			
S6	.50000	.50000	-.12500	-.16667	-.12500	--		
S7	.58333	.16667	.33333	.50000	.50000	.12500	--	
S8	.54167	.54167	.41667	.33333	.25000	.37500	.54167	--

Table 2

Principal Components Factor Matrix

	FACTOR 1	FACTOR 2	FACTOR 3
S1	.83526	-.21455	-.22689
S2	.62356	-.57118	.22574
S3	.49890	.34644	.68101
S4	.50011	.62377	.16941
S5	.44292	.40614	-.61275
S6	.41789	-.76546	-.11408
S7	.77279	.34659	-.24477
S8	.82712	-.09343	.16020

Table 3

Estimated Correlations and Residuals

	S1	S2	S3	S4	S5	S6	S7	S8
S1	.79516*	-.00883	-.02120	.08789	-.08851	-.03916	-.04332	-.13289
S2	.59216	.76603*	.02472	-.07713	.13578	-.17204	-.06199	-.06362
S3	.18787	.26694	.83270*	-.16431	.13894	.00938	-.00559	-.07272
S4	.24545	-.00620	.58097	.66790*	-.16271	.12114	-.06121	-.04918
S5	.42184	-.09411	-.05561	.37105	.73659*	-.06911	-.13304	.01975
S6	.53916	.67204	-.13438	-.28781	-.05589	.77358*	.03943	-.02389
S7	.62666	.22866	.33892	.56121	.63304	.08557	.77725*	-.02594
S8	.67456	.60528	.48938	.38251	.23025	.39889	.56760	.71852*

The lower left triangle contains the reproduced correlation matrix: the diagonal, communalities; and the upper right triangle, residuals between the observed correlations and the reproduced correlations.

Table 4

Rotated Principal Components Factor Matrix

	FACTOR 1	FACTOR 2	FACTOR 3
S1	.70317	.53231	.13176
S2	.85458	-.06075	.17897
S3	.12088	-.03052	.90397
S4	-.11642	.44821	.67339
S5	-.04362	.85672	-.02676
S6	.83907	-.03069	-.26190
S7	.24474	.76286	.36796
S8	.63283	.31558	.46740

Table 5

Principal Components Factor Matrix

	FACTOR 1	FACTOR 2
S1	.83526	-.21455
S2	.62356	-.57118
S3	.49890	.34644
S4	.50011	.62377
S5	.44292	.40614
S6	.41789	-.76546
S7	.77279	.34659
S8	.82712	-.09343

Table 6

Rotated Principal Components Factor Matrix

	FACTOR 1	FACTOR 2
S1	.45130	.73485
S2	.05121	.84407
S3	.59947	.09776
S4	.79312	-.10078
S5	.60073	.01592
S6	-.23168	.84077
S7	.79647	.28804
S8	.52966	.64212

Table 7

Principal Components Factor Scores

FSCORE1	FSCORE2
.17579	-1.19704
-1.33861	.86867
.05309	.81253
.54774	.23919
.56165	-.67283
-.19632	1.45992
.48985	-.36663
.26978	-.18904
.42500	1.19128
.04374	1.27822
1.15418	-1.17111
2.04290	-1.01439
.48025	1.65890
-.88405	-.97153
-.38641	.34030
-1.73372	-1.19958
.35152	-.34958
-2.05638	-.71731

Table 8

Factor Scores on the Statements Which Defined and Differentiated the Clusters

Agree/Disagree	Statement	Score for Item I	II	I-II
	FACTOR I			
AGREE				
	Student's performance/behavior difficulties can be explained primarily by environmental, cultural, or economic disadvantage	2.04	-1.01	3.05
	Student performs much better in one or more academic subjects than in another.	1.15	-1.17	2.32
DISAGREE				
	Student displays deficits in adaptive behavior when compared to age peers.	-1.34	.87	2.21
	Student's performance/behavior difficulties can be explained primarily by general health factors.	-2.06	-.72	1.34
	Student's performance/behavior difficulties can be explained primarily by visual, hearing, or motoric handicaps.	-1.73	-1.20	.53
	FACTOR II			
AGREE				
	Student displays inappropriate behavior or feelings under normal circumstances.	-.20	1.46	1.66
	Student's educational performance is adversely affected by his/her inappropriate behavior.	.04	1.28	1.24
	Inappropriate behavior/feelings have been exhibited over an extended period of time and to a significant degree.	.48	1.66	1.18
	Student has difficulty focusing and sustaining attention, and/or appears impulsive, hyperactive, or distractible.	.42	1.19	.77
DISAGREE				
	Student has difficulty discriminating visually or auditorily, may appear disorganized.	.18	-1.20	1.38

Figure 1

Principal Components Analysis - Orthogonal Rotation

Figure 2

Principal Components Analysis - Orthogonal Rotation

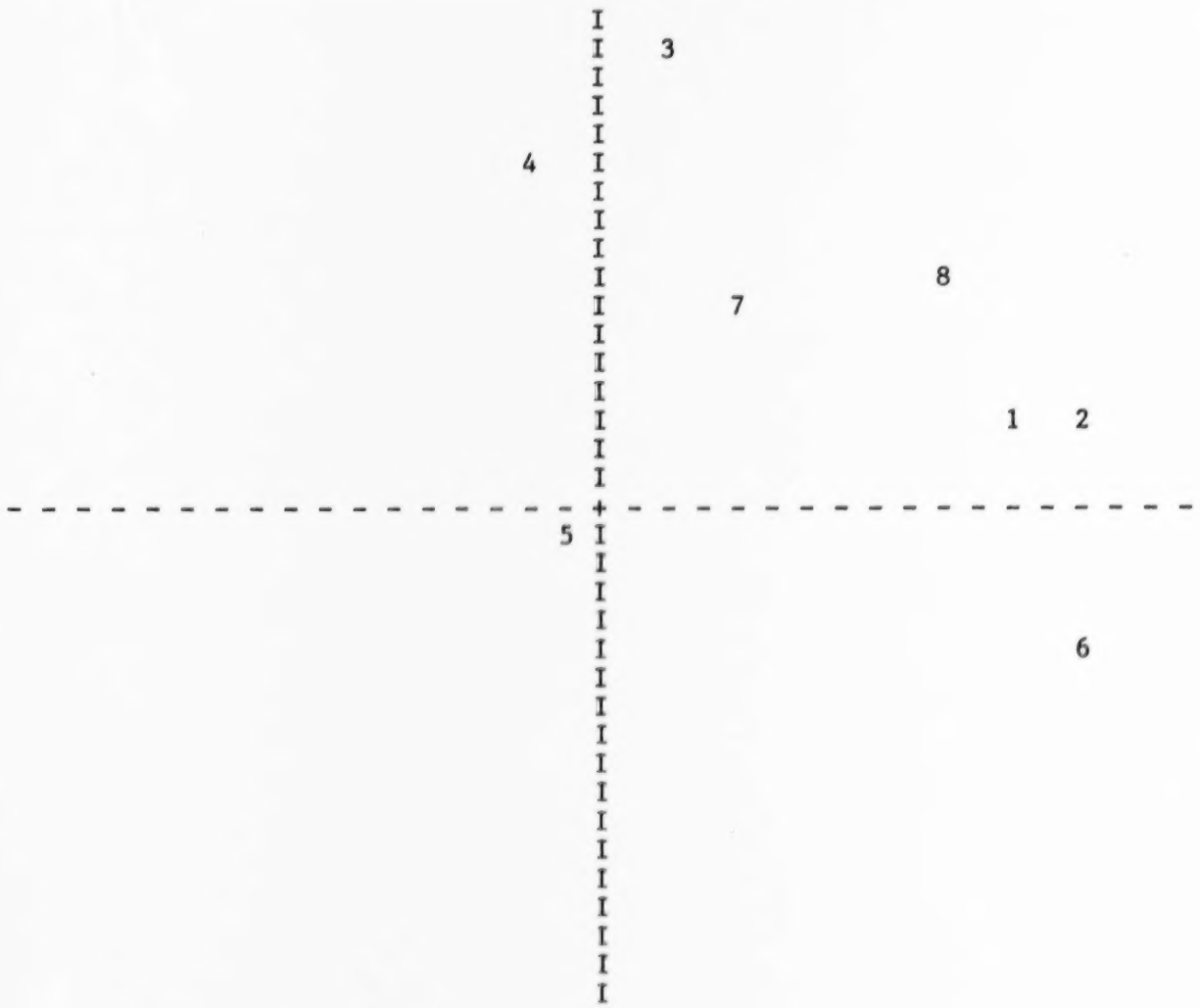


Figure 3

Principal Components Analysis - Orthogonal Rotation

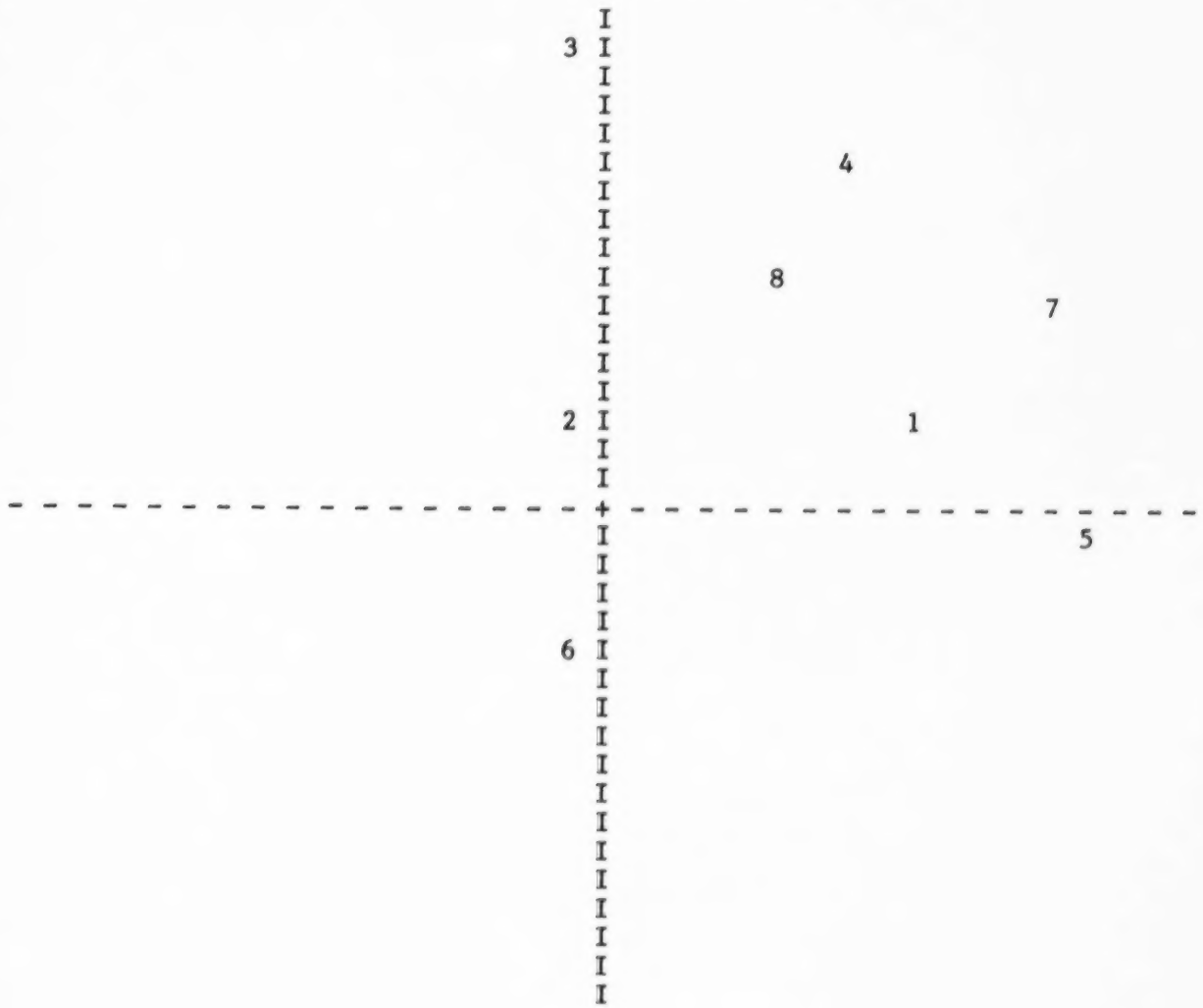


Figure 4

Principal Components Analysis - Orthogonal Rotation

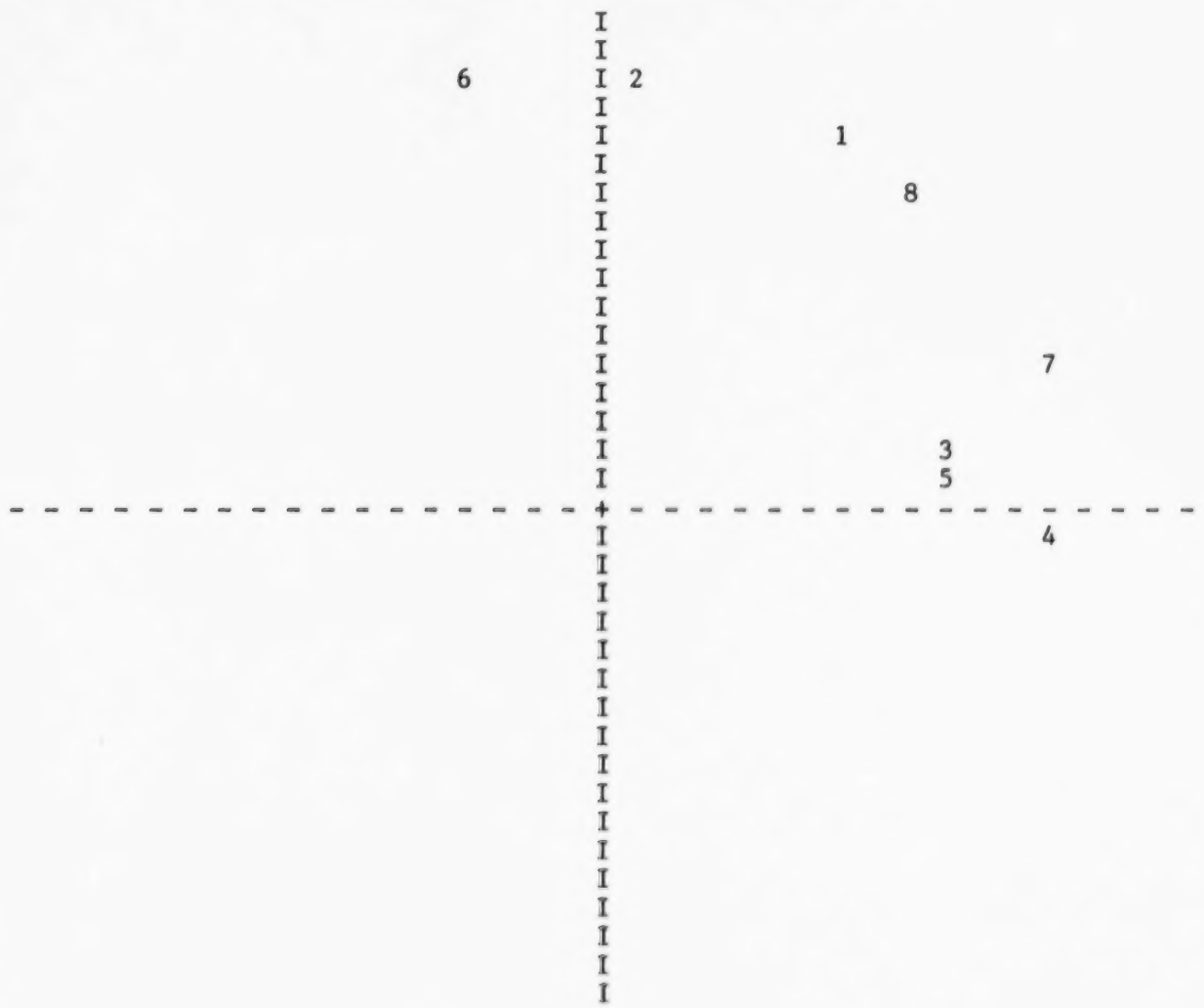
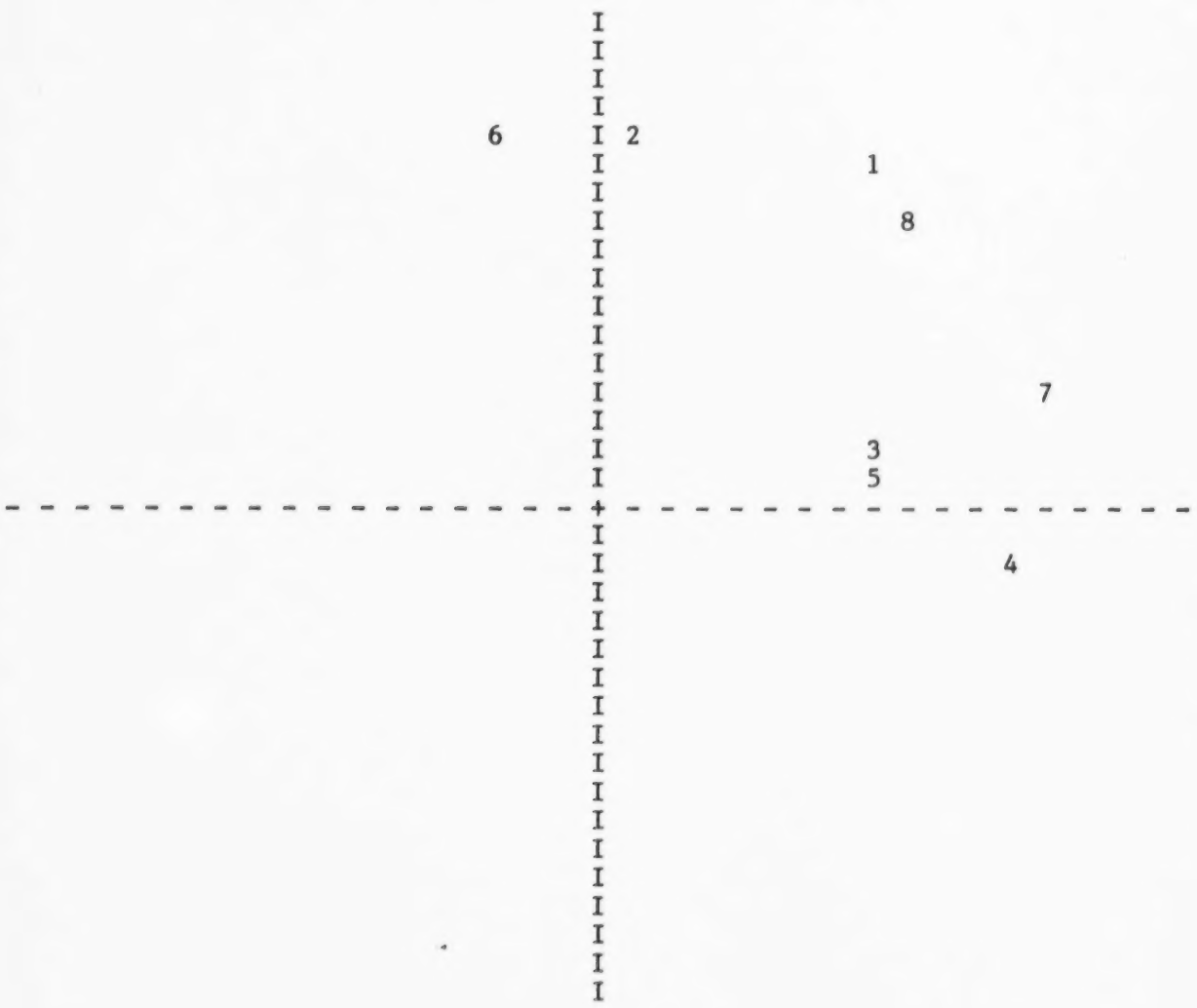


Figure 5

Principal Factors Analysis - Orthogonal Rotation



Appendix A: Q-Technique Data File

S1	S2	S3	S4	S5	S6	S7	S8
2	3	4	4	2	1	2	2
3	3	2	2	2	5	2	3
4	4	3	3	4	4	3	3
3	3	3	4	3	3	3	5
3	3	4	4	3	2	3	2
4	5	3	3	4	5	3	3
3	2	5	3	3	3	3	3
3	3	3	1	5	2	4	3
4	4	3	4	2	4	4	5
5	4	3	3	3	4	3	4
4	1	2	5	4	2	4	2
2	2	5	5	4	2	5	4
5	5	4	3	2	4	5	4
2	3	2	2	3	1	1	2
2	4	4	2	3	3	2	4
1	1	2	2	1	3	1	1
3	2	1	3	5	3	4	3
1	2	1	1	1	3	2	1

Appendix B: SPSS-X Command File Used to Analyze Q-Technique Data

```
TITLE 'QTECHNIQUE'
FILE HANDLE SCC/NAME='QTECH.DAT'
DATA LIST FILE=SCC/S1 TO S8 1-8
LIST VARIABLES=ALL/CASES=500
SUBTITLE '@@@ PRIN COMP'
FACTOR VARIABLES=S1 TO S8/ANALYSIS=S1 TO S8/PRINT=ALL/
   EXTRACTION=PC/ROTATION=VARIMAX/PLOT=EIGEN ROTATION
   (1 2)(1 3)(2 3)
SUBTITLE '$$$ PRIN FACTORS'
FACTOR VARIABLES=S1 TO S8/ANALYSIS=S1 TO S8/PRINT=ALL/
   EXTRACTION=PAF/ROTATION=VARIMAX/PLOT=EIGEN ROTATION
   (1 2)(1 3)(2 3)
SUBTITLE '### PRIN COMP - TWO FACTORS'
FACTOR VARIABLES=S1 TO S8/ANALYSIS=S1 TO S8/PRINT=ALL/
   CRITERIA=FACTORS(2) ITERATE(50)/EXTRACTION=PC/ROTATION=
   VARIMAX/PLOT=EIGEN ROTATION(1 2)/SAVE REG (ALL FSCORE)
LIST VARIABLES=FSCORE1 FSCORE2/CASES=500
SUBTITLE '&&& PRIN FACTORS - TWO FACTORS'
FACTOR VARIABLES=S1 TO S8/ANALYSIS=S1 TO S8/PRINT=ALL/
   CRITERIA=FACTORS(2) ITERATE(50)/EXTRACTION=PAF/ROTATION=
   VARIMAX/PLOT=EIGEN ROTATION (1 2)
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